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Agent-Based Approaches for Adaptive Building HVAC System Control

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ABSTRACT

One promising technique for improving building control system performance is through the use of autonomous, intelligent agents. Agent-based methods have been proposed and demonstrated in a number of fields including control applications, but their potential in building control systems is only beginning to be investigated. This paper examines how agent-based methods could be incorporated into the operation of building control systems, thereby improving building energy performance, comfort and utility. Applications involving on-site power generation, renewable energy sources, thermal storage and grid integration present unique challenges and opportunities for high performance buildings. Approaches for integrating components and systems are discussed and demonstrated with an example using combined heat and power, absorption chiller and thermal storage.

1. INTRODUCTION

It is widely acknowledged that limitations and failures in building control systems are preventing buildings from operating at or near their full potential, in terms of energy efficiency and thermal performance. These problems are not due to a lack of high quality equipment or to an abundance of poorly trained designers, but reflect a more fundamental set of issues associated with the challenge of designing, installing, commissioning and operating complex control systems that must be able to perform under widely varying environmental conditions and occupant factors for an extended period of time. Changes in building usage, source energy costs and availability, and system modifications usually cannot be anticipated by the control system designer, making their accommodation problematic. In addition to those issues, integrating the various sub-systems to optimize their combined energy performance requires extremely detailed knowledge of equipment performance profiles, environmental factors and advanced control strategies, and such information is not always readily available.

The traditional role of building control systems is thought of as controlling heating and cooling equipment, usually by modulating fluid flows and cycling equipment as needed to maintain setpoints. While this remains an important function, high performance buildings are incorporating more innovative designs with more complicated systems, including combined heat and power (CHP), absorption chillers, thermal storage and solar thermal and photovoltaic systems. In addition, some building envelope features, particularly glazings and shading, may be capable of dynamic variation, and may be manipulated to control heat transfer and daylighting conditions. Controlling all of these systems to attain optimum performance under a wide range of dynamic conditions requires sophistication beyond that normally provided by typical building control systems.

Designing and implementing effective building control systems is not as easy task for a number of reasons. First, building designs are not standardized as each building has a unique set of requirements associated with its location and use. Buildings are not like automobiles which are produced in mass quantities with many interchangeable parts and a limited, well-defined set of functions, all being the responsibility of an integrated design team. Rather, many buildings, even those which appear to be nearly identical, have different features and combinations of components and equipment assembled on-site into larger systems and structures, usually by different sub-contractors and from different vendors. Ensuring that everything is operating properly, both at installation and over the life of the building requires a significant effort and expertise, along with considerable time and expense. Shifting some of the burden of establishing and maintaining proper building control system performance from humans to automated systems could make it possible to improve performance at a reduced cost. The pathway for achieving this is through autonomous, intelligent control systems.

2. BACKGROUND

Autonomous systems are those that are capable of acting on their own behalf, while intelligent systems have the capacity to perceive some elements of their environment and take appropriate actions. Of course, there is a wide spectrum of capabilities in both of these areas, and no clear definition of the minimum set of abilities that would qualify a system as being a member of either class. However, it is generally accepted in the field of artificial intelligence that at least some aspects of human intelligence can be replicated in machines or software to obtain certain useful behavior [Passino, 2005]. Some common intelligence traits include reasoning, knowledge, planning, learning, communication and perception. These traits can be implemented in hardware or software in different ways to the same end, ranging from highly centralized to widely distributed topologies, and based on different algorithms and structures. One approach involves the use of intelligent agents, which are a particular way of implementing autonomous, intelligent systems, and which have characteristics that make them well suited for control functions. Agent-based methods have been proposed and demonstrated in a number of fields including buildings [Zeng et al., 2008] and control applications [Davidsson et al., 2003], but their potential in building control systems has not been extensively evaluated.

How does this apply to building control systems? We can be reasonably confident that given enough time, money and expertise, we can design and implement a building control system that will function properly (as designed) after commissioning. However, we would be less confident that proper operation would persist over time as components age and degrade. More so, obtaining optimum performance would be unlikely, since environmental and occupant factors are nearly impossible to predict during design, so the basic control sequences will be compromise strategies. Agent-based methods can conceivably be applied to building control systems in the following ways:

- To enable control system components and subsystems to organize and configure themselves for basic operation
- To provide the ability of the control system to learn, adapt and optimize building performance based on dynamic occupant factors and environmental conditions
- To ensure that performance faults are detected and recognized when they occur
- To allow system upgrades and retrofit activities
- To facilitate interactions with utility grids and community or area-wide networks
- To promote the integration of innovative building energy systems

In its most basic form, an intelligent agent is an entity that can perceive something in its environment (from a perceptor or sensor) and then apply some rule or other reasoning to take an action (see Figure 1). The rules or reasoning methods can be simple or complex and the actions can vary widely, depending upon the desires of the implementer. Depending on their intended use and inherent capabilities, agents can be classified into five basic groups, as shown in Table 1:

Table 1. Basic Agent Classifications

Type of Agent	Agent Capabilities and Typical Application
1.simple reflex agents	Operates according to a *condition then action* rule(s)
2.model-based reflex agents	Maintains *internal model* of part of its environment, then chooses an action like a reflex agent
3.goal-based agents	Stores information regarding *desirable states*, then chooses an action to try to attain a desirable state
4.utility-based agents	Distinguish among possible states on the basis of some *utility function* or metric to select goal state
5.learning agents	Able to operate in an unknown environment and *accumulate knowledge* to improve performance

There are other sub-classes of agents as well as ways of describing agent processes and features, but these five groups are sufficient for a discussion of the possible application of agents to building control systems. The specific implementation of agents in a control system will not be addressed, as this requires detailed information beyond the scope of this paper. In an actual installation, agents would need to be instantiated in software and allowed to communicate and interact with each other and their environment. Agent behavior can be simulated by modeling agents and their environments using agent platforms, however, the intent of this paper is to focus on the types of agents, information modeling and communication that would be required to implement an agent-based building control system.

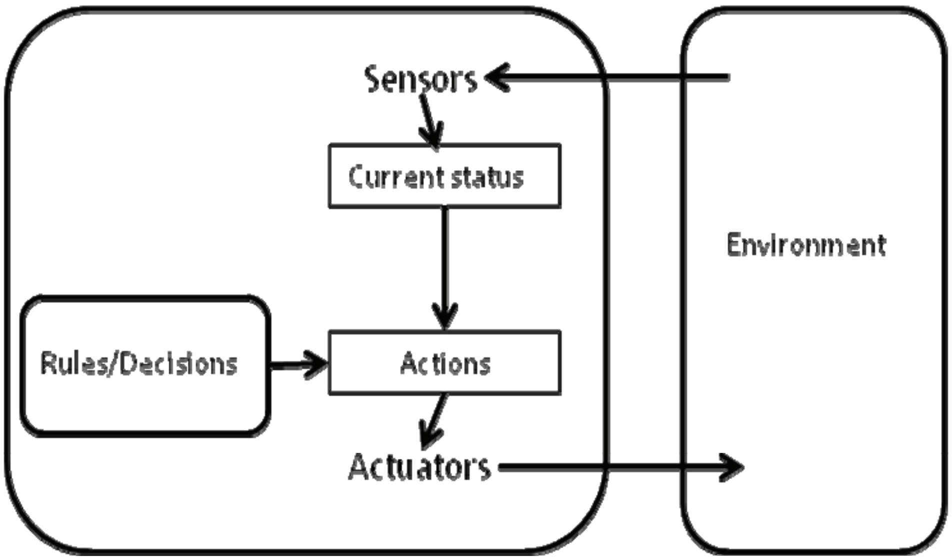

Figure 1. Schematic of intelligent agent structure

The usefulness of intelligent agents for control purposes lies in their ability to break a complex problem down into manageable elements that can be made the responsibility of individual agents or agent teams. Agents could represent physical devices, such as air handlers or hydronic coils, or represent virtual concepts, such as energy management or demand reduction. The types of agents would be matched to the tasks, and the resulting agent structure would, in most cases, be distributed and layered, with some agents performing simple tasks such as controlling temperatures and flow rates, while others have more complex tasks, for example to minimize energy usage or cost, or detect and rectify problems. The agent framework would be a virtual overlay representation of the physical system, and the physical sensors and actuators would be controlled by the actions of the agents as they interact with each other and the environment and building occupants. The control strategies that would be possible would be decoupled from the constraints imposed by typical control system feedback loops and fixed sequences of operation. In particular, control strategies could evolve by learning from their environment and adapt to optimize the dynamic performance of the building energy systems.

3. ADAPTIVE CONTROL, OPTIMIZATION AND INTELLIGENT AGENTS

The objective of an optimization process is to minimize or maximize some function, such as energy usage, cost or comfort, usually subject to some constraints on operating conditions. For example, if we wish to minimize total HVAC system power represented by an approximator function (J) with respect to a forcing function (f) consisting of all uncontrolled variables (load and environmental conditions and occupant factors), by manipulating continuous control variables (u) and discrete control variables (M), we have:

$$\min J = \min J(f,u,M) \tag{1}$$

The elements of u are temperature setpoints, air and water flow rates, etc., while M consists of equipment with discrete settings such as on/off, multi speed, etc., or systems with parallel means for providing the same service, such as multiple chillers or heat sources. One approach to optimizing J would be to determine its shape from modeling, and then to try to find locations where ($dJ/du = 0$) (f and M may vary, but presumably at a slower rate). The difficulty of this task depends on the complexity of the function J; specifically whether it has many hills and valleys that may tend to fool the solution technique into selecting a local rather than global minimum [Wetter et al., 2004]. An alternate approach would be to observe the behavior of J under actual operation and develop a data-driven model of the relationship between J and u and M.

Model-based optimization has been presented by [Braun et al., 1989] who developed a methodology for determining an optimal control strategy for an HVAC system, and [Pape, et al., 1991], who used an empirical cost function approach to investigate the effect of chilled water supply temperature and supply air temperature on overall HVAC system power usage. Subsequently, [Ahn et al., 2001], extended this work to include the effect of condenser/cooling tower operation, and used a quadratic representation of total system power requirements. [Yu et al., 2007] used a sophisticated model to investigate the part load performance of air-cooled chillers with variable speed condenser fan control, and [Treado, 2010] presented a gradient method for selecting optimum setpoints for HVAC systems.

Agent-based methods can be used to implement model-based or data-driven optimization approaches, using either model-based agents or learning agents, along with utility-based agents. The capabilities of each component could be imbedded within using a common data structure similar to the Transducer Electronic Data Sheet (TEDS) developed by the IEEE 1451 Standard [IEEE, 2007] and a standard communication protocol such as ASHRAE Standard 135-BACnet [ASHRAE, 2008]. Lower level agents would represent each component, such as sensors, actuators, fans, pumps and controllers, each of which would be able to manage their basic operation using simple rules. The agents would initially query each other and build a relational data structure to provide context for their operation. Higher level agents would be responsible for operational strategies, such as setting and adjusting setpoints, monitoring space conditions and energy usage, and responding to occupant and environmental factors. The highest level agents would provide more abstract functions, such as demand limiting and fuel switching, based on goal setting and utility functions. Learning could be implemented at any level, but would be tailored to the specific agent functions (i.e., individual agents would only need to learn how to do their job better). This type of agent structure, termed multi-level, multi-agent, is shown schematically in Figure 2. In this figure, the class of agents labeled Agent 1 are trying to maintain process outputs (i.e. temperatures, flow rates) equal to the setpoints, while the class of agents labeled Agent 2 are directing the class 1 agents to modulate setpoints as needed to achieve the best integrated performance for several sub-systems. They do this by looking at multiple outputs and applying higher level rules, possibly based on simple models or goal states. Agent 3 is monitoring environmental conditions and learning how to optimize control system operation by maximizing utility. This structure can extend both horizontally and vertically to accommodate a wide range of system scales, provided that component properties are consistently represented and communication is standardized.

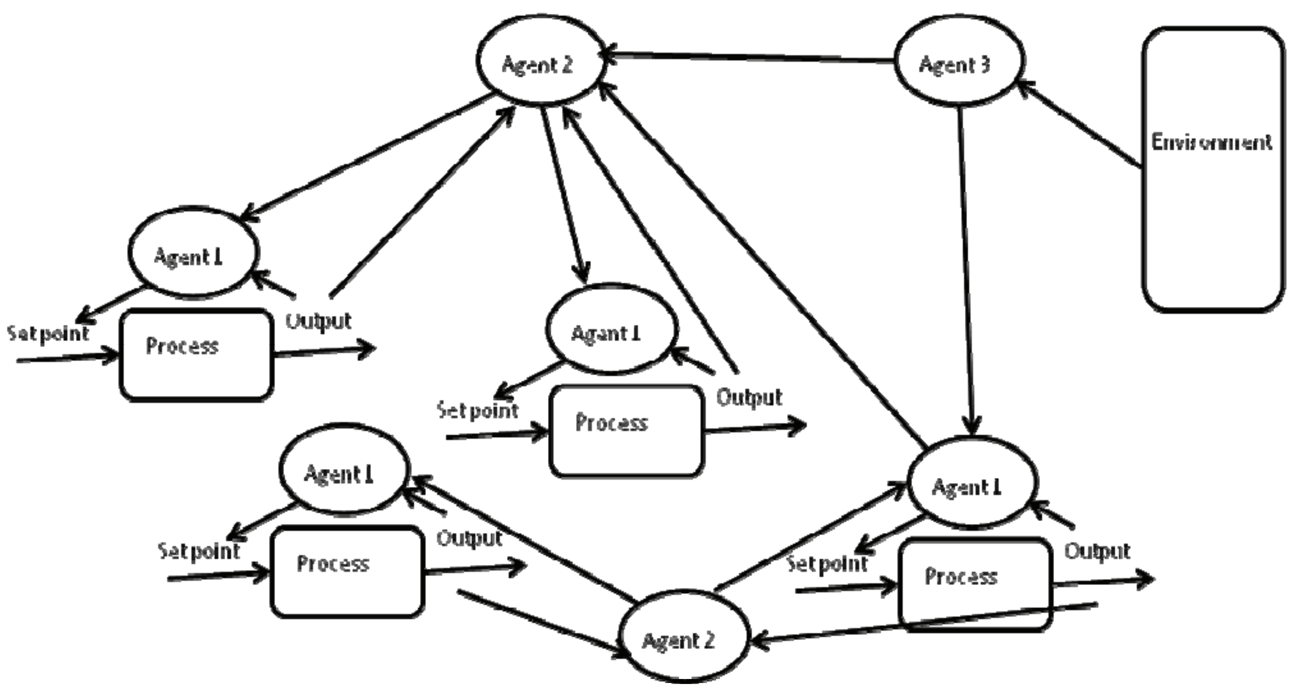

Figure 2. Schematic of multi-level, multi-agent framework

4. EXAMPLE OF AN ENERGY SYSTEM FOR A HIGH PERFORMANCE BUILDING

Figure 3 shows a schematic of an energy system for a high performance building consisting of a combined heat and power system (CHP), absorption (ABS) and electric chillers (EL), and thermal storage (TS). The building has heating, cooling and electric power requirements that vary throughout the day and on a seasonal basis, and excess electrical power can be sold to the utility. There are many possible operating modes for the system depending on the various loads, and the optimum operating strategy is a function of electric and fuel unit costs, electric power buyback rates, and the dynamic needs for thermal energy. For example, for any heating load, cooling load and electrical load combination, the system could be operated to:

1. Try to meet the electric load with the CHP, and use as much waste heat as possible to meet the cooling load with the absorption chiller, relying on the electric chiller to meet any remaining cooling load with utility power
2. Use the CHP to meet the electric load and run the electric chiller, and use waste heat to run the absorption chiller
3. Use the CHP to meet the electric load and use the waste heat for the heating load
4. Sell electrical power to the utility
5. Store excess waste heat for future use
6. Various intermediate combinations

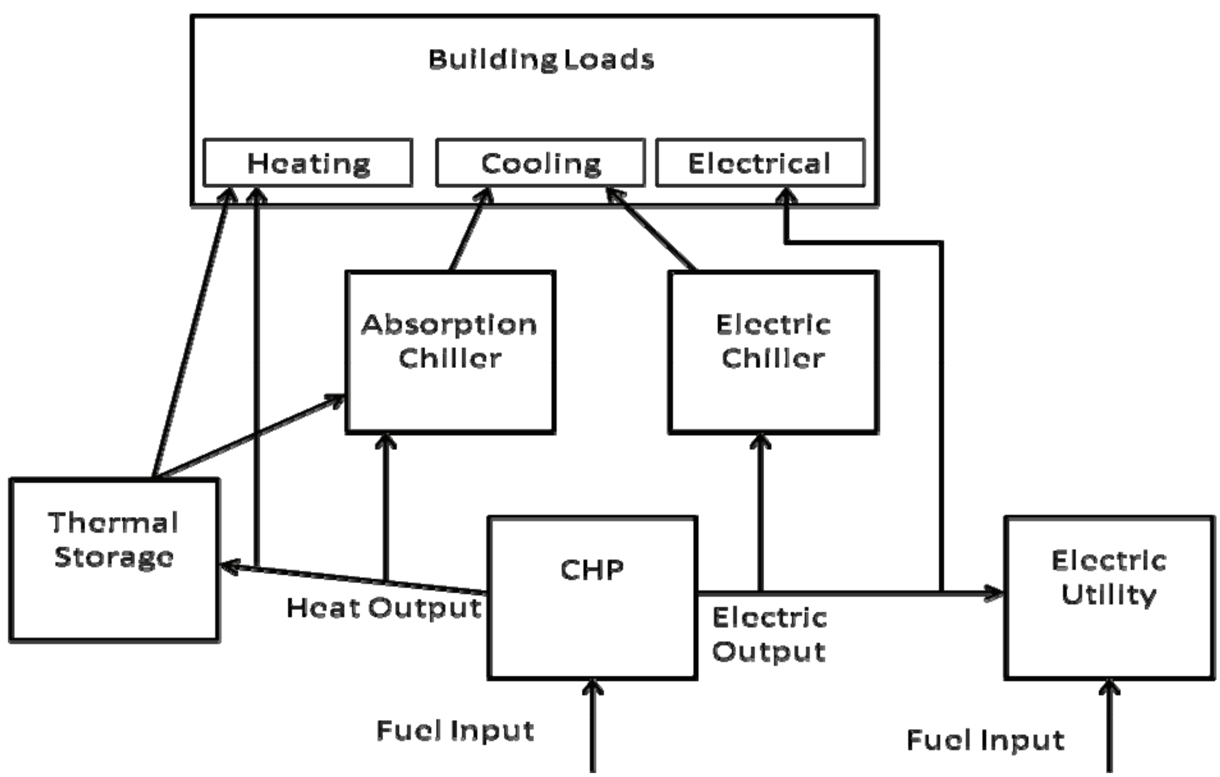

Figure 3. High performance building energy system

Configuring and operating this system requires determining setpoints for fluid temperatures and flow rates, as well as decisions regarding operating points and energy flows, all of which could vary with weather conditions, energy costs and occupant requirements. This means controlling pumps, fans, valves, dampers and other equipment so that they operate properly as components, while providing optimum integrated performance. The system components and their primary input and output points are identified in Table 2.

Table 2. System Component Input and Output Points

Component	Sensors/Inputs	Outputs	Derived Values
CHP- 50 kW rating	Electrical power output	Fuel input	Part load ratio
	Waste heat output		
	Waste heat temperature		
ABS- 18 kW rating	Cooling effect	Absorber pump	Part load ratio
	Generator heat input		COP
	Generator inlet water temperature		
	Condenser inlet water temperature		
	Evaporator outlet water temperature		
EL- 20 kW rating	Cooling effect	Compressor	Part Load ratio
	Electrical power input	Hot gas bypass	COP
	Leaving chilled water temperature		
	Entering condenser water temperature		
TS	Storage temperature		Stored energy
			Remaining storage capacity
Water loops	Mass flow rates	Pump speeds	Energy delivery or extraction rate
	Discharge temperatures	Throttling valve percentages	
		Routing valve positions	

This system was simulated in MATLAB using the mathematical models listed in the Engineering Reference Manual for Energy Plus [Energy Plus, 2009]. These models relate energy inputs and outputs of equipment and sub-systems to operating parameters and environmental conditions, some of which are determined by the control system (setpoints), and others which are due to environmental conditions and occupant factors (heating, cooling and electrical loads). Simple agents were simulated to control setpoints, and different cooling and electric load ratios were assumed in order to demonstrate how the system could be controlled under steady state conditions. There are many different operating modes that are possible, and the intent of the simulations was not to try to find optimum combinations for this particular system, but rather to illustrate how they could be attained.

The starting point for the simulation was to assume that the CHP system would be operated at a fixed load, such as 80% of full load, or 40 kW electrical output. One example had an electric load of 32 kW and a cooling load of 30 kW, and an unspecified heating load. Since the cooling load is greater than the capacity of each individual chiller, some combination of chiller loads will be required, such that the sum of the two chiller loads will equal the total cooling load. Cooling with the absorption chiller makes efficient use of the CHP waste heat, and the electrical power produced can help drive the electric chiller. However, depending on how much heat is used for the absorption chiller, there will be more or less heat available to meet other heating loads for the building, such as space and water heating, as shown in Figure 4. Similarly, depending on how much of the cooling load is met by the electric chiller using electrical power from the CHP system, there will be more or less excess electrical power available for other uses or to sell to the grid, as shown in figure 5.

The total cost for energy for heating, cooling and electricity consists of the fuel cost to run the CHP system plus the net electrical cost, plus any supplemental heating energy. Figure 6 shows the cost for the CHP fuel and electrical power, without including any supplemental heating energy costs. This figure assumes that electrical power can be purchased for $0.10 per kWh but sold for only $0.05 per kWh, as is sometimes the case, and $0.034 per kWh for fuel input. The fuel cost is constant since the CHP electrical power output is held constant for this example, and a negative excess electric power indicates the need to purchase power from the utility. The choice of how to apportion the cooling load to the two chillers depends on the need for heating for other purposes. Excess heat can either be used immediately or sent to thermal storage for future use. The management of these processes can be delegated to agents with responsibilities for monitoring system outputs, load requirements and energy inputs and costs. Total energy cost could be a utility function, and dynamic performance could be tailored by modeling and learning agents.

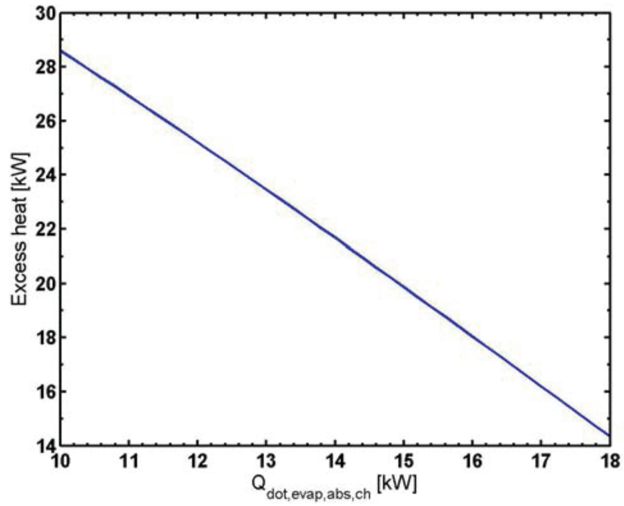

Figure 4. Excess heat versus evaporator cooling effect for the absorption chiller

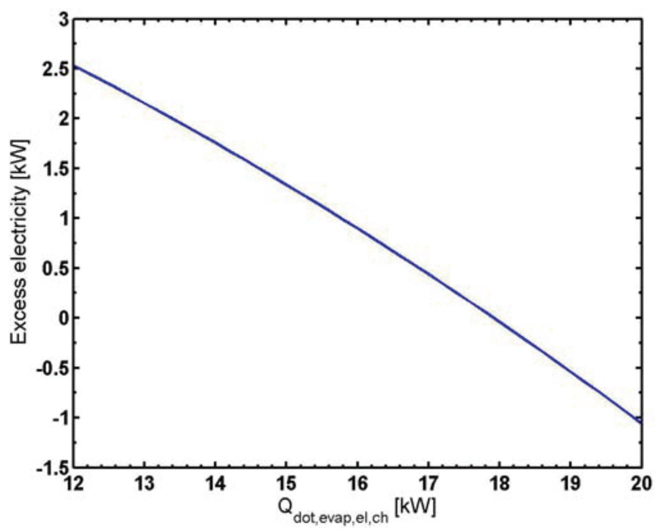

Figure 5. Excess electricity versus evaporator cooling effect for the electric chiller

5. CONCLUSION

Adaptive intelligent control of building systems holds great promise for improving building energy system performance, and reaching the goal of high performance or zero-energy buildings. However, traditional building control system design and operation are not capable of producing building control systems that can reach the full potential, due to inherent limitations in control strategies, and lack of adaptability and resources. The emerging development of agent-based intelligent systems may circumvent these problems by providing a robust platform for autonomous control system configuration and operation, enabling adaptability, optimization and long-term reliable performance.

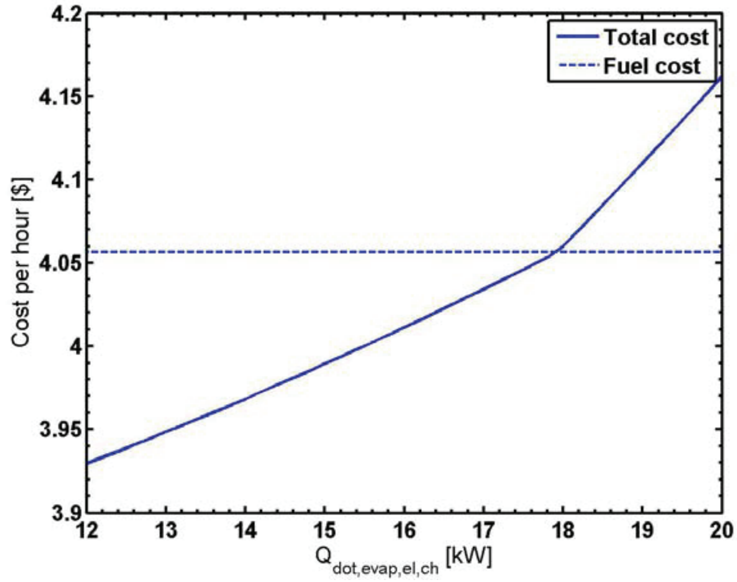

Figure 6. Cost versus evaporator cooling effect for the electric chiller

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